Statistical Modeling and Analysis of Neural Data (NEU 560)
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Lecture 3B notes: Least Squares Regression

1 Least Squares Regression

Suppose someone hands you a stack of N vectors, $\{\vec{x}_1, \dots \vec{x}_N\}$, each of dimension d, and an scalar observation associated with each one, $\{y_1, \dots, y_N\}$. In other words, the data now come in pairs $(\vec{x}_i, y_i)$, where each pair has one vector (known as the *input*, the *regressor*, or the *predictor*) and a scalar (known as the *output* or *dependent variable*).

Suppose we would like to estimate a linear function that allows us to predict y from $\vec{x}$ as well as possible: in other words, we'd like a weight vector $\vec{w}$ such that

$$y_i \approx \vec{w}^\top \vec{x}_i.$$

Specifically, we'd like to minimize the squared prediction error, so we'd like to find the $\vec{w}$ that minimizes

$$\text{squared error} = \sum_{i=1}^{N} (y_i - \vec{x}_i \cdot \vec{w})^2 \tag{1}$$

We're going to write this as a vector equation to make it easier to derive the solution. Let Y be a vector composed of the stacked observations $\{y_i\}$, and let X be the vector whose rows are the vectors $\{\vec{x}_i\}$ (which is known as the *design matrix*):

$$Y = \begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} \qquad X = \begin{bmatrix} — & \vec{x}_1 & — \\ & \vdots & \\ — & \vec{x}_N & — \end{bmatrix}$$

Then we can rewrite the squared error given above as the squared vector norm of the residual error between Y and $X\vec{w}$:

$$\text{squared error} = ||Y - X\vec{w}||^2 \tag{2}$$

The solution (stated here without proof): the vector that minimizes the above squared error (which we equip with a hat $\hat{\vec{w}}$ to denote the fact that it is an estimate recovered from data) is:

$$\vec{w} = (X^\top X)^{-1}(X^\top Y).$$

2 Derivation #1: using orthogonality

I will provide two derivations of the above formula, though we will only have time to discuss the first one (which is a little bit easier) in class. It has the added advantage that it gives us some insight into the geometry of the problem.

Let's think about the design matrix X in terms of its d columns instead of its N rows. Let $\{X_j\}$ denote the $j'th$ column, i.e.,

$$X = \begin{bmatrix} | & & | \\ X_1 & \cdots & X_d \\ | & & | \end{bmatrix} \tag{3}$$

The columns of X span a d-dimensional subspace within the larger N-dimensional vector space that contains the vector Y. Generally Y does not lie exactly within this subspace. Least squares regression is therefore trying to find the linear combination of these vectors, $X\vec{w}$, that gets as close to possible to Y.

What we know about the optimal linear combination is that it corresponds to dropping a line down from Y to the subspace spanned by $\{X_1, \ldots X_D\}$ at a right angle. In other words, the error vector $(Y - X\vec{w})$ (also known as the *residual error*) should be orthogonal to every column of X:

$$(Y - X\vec{w}) \cdot X_j = 0, \tag{4}$$

for all columns $j = 1$ up to $j = d$. Written as a matrix equation this means:

$$(Y - X\vec{w})^\top X = \vec{0} \tag{5}$$

where $\vec{0}$ is d-component vector of zeros.

We should quickly be able to see that solving this for $\vec{w}$ gives us the solution we were looking for:

$$X^\top(Y - X\vec{w}) = X^\top Y - X^\top X\vec{w} = 0 \tag{6}$$

$$\implies \quad (X^\top X)\vec{w} = X^\top Y \tag{7}$$

$$\implies \quad \vec{w} = (X^\top X)^{-1} X^\top Y. \tag{8}$$

So to summarize: the requirement that the residual errors $Y - X\vec{w}$ be orthogonal to the columns of X was all we needed to derive the optimal weight vector $\vec{w}$. (Hooray!)

3 Derivation #2: Calculus

3.1 Calculus with Vectors and Matrices

Here are two rules that will help us out for the second derivation of least-squares regression. First of all, let's define what we mean by the gradient of a function $f(\vec{x})$ that takes a vector $(\vec{x})$ as its input. This is just a vector whose components are the derivatives with respect to each of the components of $\vec{x}$:

$$\nabla f \triangleq \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \vdots \\ \frac{\partial f}{\partial x_d} \end{bmatrix}$$

Where ∇ (the "nabla" symbol) is what we use to denote gradient, though in practice I will often be lazy and write simply $\frac{df}{d\vec{x}}$ or maybe $\frac{\partial}{\partial \vec{x}} f$.

(Also, in case you didn't know it, $\triangleq$ is the symbol denoting "is defined as").

Ok, here are the two useful identities we'll need:

1. Derivative of a linear function:

$$\frac{\partial}{\partial \vec{x}}\, \vec{a} \cdot \vec{x} \quad = \quad \frac{\partial}{\partial \vec{x}}\, \vec{a}^\top \vec{x} \quad = \quad \frac{\partial}{\partial \vec{x}}\, \vec{x}^\top \vec{a} \quad = \quad \vec{a} \tag{9}$$

   (If you think back to calculus, this is just like $\frac{d}{dx}\, ax = a$).

2. Derivative of a quadratic function: if A is symmetric, then

$$\frac{\partial}{\partial \vec{x}}\, \vec{x}^\top A \vec{x} = 2A\vec{x} \tag{10}$$

   (Again, thinking back to calculus this is just like $\frac{d}{dx}\, ax^2 = 2ax$).

   If you ever need it, the more general rule (for non-symmetric A) is:

$$\frac{\partial}{\partial \vec{x}}\, \vec{x}^\top A \vec{x} = (A + A^\top)\vec{x},$$

   which of course is the same thing as $2A\vec{x}$ when A is symmetric.

3.2 Calculus Derivation

We can call this derivation (i.e., the $\vec{w}$ vector that minimizes the squared error defined above) the "straightforward calculus" derivation. We will differentiate the error with respect to $\vec{w}$, set it equal to zero (i.e., implying we have a local optimum of the error), and solve for $\vec{w}$. All we're going to need is some algebra for pushing around terms in the error, and the vector calculus identities we put at the top.

Let's go!

$$\frac{\partial}{\partial \vec{w}}\, SE = \frac{\partial}{\partial \vec{w}}\, (Y - X\vec{w})^\top (Y - X\vec{w}) \tag{11}$$

$$= \frac{\partial}{\partial \vec{w}} \left(Y^\top Y - 2\vec{w}^\top X^\top Y + \vec{w}^\top X^\top X \vec{w} \right) \tag{12}$$

$$= -2X^\top Y + 2X^\top X\vec{w} \quad = \quad 0. \tag{13}$$

We can then solve this for $\vec{w}$ as follows:

$$X^\top X \vec{w} = X^\top Y \tag{14}$$

$$\implies \quad \vec{w} = (X^\top X)^{-1} X^\top Y \tag{15}$$

Easy, right?

(Note: we're assuming that $X^\top X$ is full rank so that its inverse exists, implying that $N > d$ and the rows are not all linearly dependent.)